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Airline horizontal mergers and productivity: Empirical evidence from a quasi-natural experiment in China

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ABSTRACT

The identification of possible efficiency gains is a core issue in the analysis of mergers. However, empirical studies are generally subject to bias caused by merger endogeneity. In the early 2000s, the Chinese government pursued a strategy of merging small firms in key industries to create large enterprise groups. Mergers created by this policy provide a rare quasi-natural experiment to investigate the effect of mergers. We take the opportunity to apply the difference-in-differences approach to identify the effect of mergers on the efficiency of Chinese airlines. Overall, our analysis suggests that the mergers increased the productivity of Chinese airlines.

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1. Introduction

This study aims to identify the effect of mergers on airline efficiency using the merger cases of Chinese airlines in the early 2000s. Identifying the possible efficiency gains from a merger is a core issue in merger evaluation. The US Horizontal Merger Guideline (U.S. Department of Justice and the Federal Trade Commission, 2010) noted that the "*primary benefit of mergers to the economy is their potential to generate significant efficiencies and thus enhance the merged firm's ability and incentive to compete, which may result in lower prices, improved quality, enhanced service, or new products.*" Scholars have made great efforts to empirically quantify the effect of mergers on productivity for various industries. A comprehensive review of such studies can be found in Kolaric and Schiereck (2014).

Major airline mergers in recent decades have created some of the world's largest airlines. These mergers have generated many policy debates around the world. Past studies (Borenstein, 1990; Kim and Singal, 1993; Prager and Hannan, 1998; Bilotkach, 2010; Kwoka and Shumilkina, 2010) have identified anti-competitive effects of airline mergers. However, as Peters (2006) pointed out, these studies normally omit supply-side factors such as cost. In the airline industry, higher traffic volumes allow the use of larger, more efficient aircraft, and more intensive utilization of aircraft, airport facilities, and ground equipment. Such "economies of density" effects have been found in empirical studies (Caves et al., 1984; Brueckner and Spiller, 1991, 1994). Moreover, increasing traffic volume leads to more frequent flights, which reduces schedule delays,[1] a major determinant of service quality for airlines (Anderson and Kraus, 1981; Richard, 2003). An increase in service quality will in turn generate positive feedback that adds to the economies of density.[2] By aggregating the traffic volumes of the firms involved, airline mergers are expected to bring efficiency gains.

However, although a number of studies directly and indirectly investigated the cost and efficiency implications of airlines mergers, empirical results are mixed. Using TFP analysis, Oum and Yu (1995) noted that Air France improved its TFP substantially since the merger with UTA in 1992. With cost function estimation, Johnston and Ozment (2013) concluded that major US airlines enjoyed increasing returns to scale which was one possible explanation for merger activities. The study on the mergers of Delta-Northwest and United-Continental led Gayle and Le (2013) to conclude that there were marginal and fixed cost savings at the route level. Chow and Fung (2012) estimated a stochastic frontier production function for Chinese airlines using an unbalanced panel data during 1997–2001. They identified efficiency improvements associated with airline mergers, although only one output, revenue-ton-kilometers, was used in their analysis. Positive effects on productivity have also been identified by case studies (Schosser and Wittmer, 2015;

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[1] Schedule delay was first proposed by Douglas and Miller (1974a, b); it refers to the difference between travelers' ideal and actual departure time.

[2] Supporting evidence was found for the SAS-Swiss alliance (Youssef and Hansen, 1994) and airline code-sharing agreements in the trans-Pacific markets (Oum et al., 1996; Park, 1997; Oum et al., 2000). Clougherty (2002) showed that US airlines' international competitiveness could be enhanced through economies of density in the domestic market.

Manuela et al., 2016) and investigations on airline alliances (Oum and Zhang, 2001; Goh and Yong, 2006).[3] On the other hand, Barros et al. (2013) did not identify any efficiency gains brought by mergers in their technical efficiency analysis of US airlines, partly because most sample carriers were involved in some mergers during the study period. The DEA analysis by Merkert and Morrell (2012) concluded that there is an interval of optimal airline size; thus the economies of scale argument for mergers holds conditionally. Based on cost function estimates for selected international airlines, Gudmundsson et al. (2017) concluded that mergers did not affect unit costs significantly, and might have led to cost increases when merging airlines were of very different sizes.

In addition to geographic and airline specific factors, the mixed findings in the literature may also arise from identification methods and research designs used. The most challenging problem that empirical studies face in attempting to identify the effects of mergers is endogeneity. Mergers are likely to be driven by efficiency concerns, and this endogeneity will bias the estimates of merger effects in empirical approaches that fail to control for it. One approach to address the endogeneity is to use instrument variables that are correlated with the merger decision but not with firm efficiency. However, finding a truly exogenous instrument variable is a daunting task. Another approach to address the endogeneity is to adopt a structural model that incorporates the model of the merger decision directly into the analysis. Examples of this structural approach can be found in Nevo (2000), Gugler and Siebert (2007) and Egger and Hahn (2010). The major criticism of this structural approach is that the model normally relies on many assumptions that are difficult to justify,[4] and thus it would be useful to check if results are consistent with credible quasi-experimental estimates[5] (Angrist and Pischke, 2010).

The mergers of Chinese airlines, the focus of our investigation, were created by the national policy pursued by the Chinese government in the early 2000s. The policy forced small state-owned firms in industries deemed as a “life-line” to the nation, such as the airline, automobile, electricity and steel industries, to merge into large, state-owned enterprise groups. The government’s main motivation in pursuing such a strategy was to strengthen its influence over the entire economy (Pearson, 2007). Because the government aimed to create airline groups of similar size, the mergers of Chinese airlines in the early 2000s were not entirely randomly arranged. However, because productive efficiency was not explicitly evaluated in the merger process, such an event can be properly treated as a quasi-natural experiment that allows us to bypass the issue of endogeneity to measure the effects of the merger on airline efficiency. We apply the difference-in-differences

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[3] For a review of the effects of airline mergers and alliances, see Yan et al. (2016).

[4] Angrist and Pischke (2010) cautioned that Nevo’s model imposed restrictions on demand substitution pattern and consumer behavior, and strong assumptions related to the validity of instrumental variable, changes in costs and competition pattern. Egger and Hahn (2010) admitted that their model was dependent on a number of strong assumptions of identification, but such an approach was justified by the "exceptionally high quality" data used.

[5] In their analysis, Hausman and Leonard (2002) reviewed the assumptions of three structure models and compared results to “direct” DID estimates. They concluded that one structural model produced similar estimates to the direct estimates. Peters (2006) examined the predictive performance of structural simulations, and found predictions of post-merger airfare seemed to be poor.

(DID) approach to identify the effects of the merger on both the total factor productivity (TFP) and operational costs of Chinese airlines. The control group in the DID estimation includes major airlines in Asia, Europe, and North America. We find that the merger increased the efficiency of the merged airlines and the finding is robust with respect to various identification assumptions.

This study complements the large number of studies reviewed by Kolaric and Schiereck (2014) on identifying the effects of mergers on firm efficiency. In particular, as a case study on airlines, this paper contributes directly to the literature on the effects of mergers and alliances on airlines' productivity. The findings provide valuable insights for industry practitioners and government regulators at a time when waves of mergers are taking place in the world's major aviation markets.

2. Industry background

The airline industry in China was under military control until it was separated from the air force in 1980. From 1987 to 1991, six major state-owned airlines were formed. The airlines and their hub airports, based in national or provincial cities, were Air China (Beijing), China Eastern (Shanghai), China Northwest (Xi'an), China Northern (Shenyang), China Southwest (Chengdu), and China Southern (Guangzhou). A number of small/regional airlines were subsequently formed, including a couple of private carriers and low cost carriers. Air fares had been progressively deregulated since 1992 (Zhang and Round, 2008), and route entry regulations were removed from all airports except those in Beijing, Shanghai, and Guangzhou (Fu et al., 2015a). From 1997 to 2004, the three largest airlines, China Eastern, China Southern, and Air China, were partially privatized through IPOs in domestic and overseas stock exchanges, although they have always been majority state owned. As of today, legacy regulations remain in areas such as aircraft purchases, pilot training and recruitment, airport charges, and slot allocations at congested airports. A few state-owned companies effectively monopolize the jet fuel supply and IT systems for ticket distribution and airport departures (Fu et al., 2015b). Thanks to strong economic growth and progressive deregulation, the number of air passengers increased at an annual rate of 14.9% from 1990 to 2010, and by 2005, China's aviation market had become the second largest in the world.

During the wave of mergers in China's life-line industries, the nine largest airlines, all of which were state-owned, were forced to merge to become three airline groups—China Eastern Airlines, China Southern Airlines, and Air China.[6] There are two notable features associated with these mergers. First, although the actual consolidations were separately carried out over the following years, they were ratified and announced on the same

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[6] Specifically, China Eastern airlines merged with China Northwest and Yunnan airlines; China Southern merged with China Northern and Xinjiang airlines; and Air China merged with China Southwest and CNAC airlines.

day,[7] and completed in 2004. Because these mergers were simultaneously imposed and led by the government, the influences of merger endogeneity and competition dynamics, which would otherwise lead to waves of mergers and endogeneity in the estimation, were reduced to a minimum. Second, the government clearly aimed to create three airline groups with comparable sizes and networks. After the mergers, the "big three" airlines (China Eastern, China Southern, and Air China) had comparable levels of registered capital, fleet sizes, and numbers of employees (Shaw et al., 2009). The merging airlines' networks were complementary to each other, thus the merged carriers each controlled one mega-hub and had comparable national networks. For example, only 12% of China National's routes and 11% of China Southwest's routes overlapped with Air China's in 2001, before the mergers. Similar patterns held for the other two airline groups. In this sense, these mergers were not entirely randomly arranged. However, airlines' productive efficiency was not benchmarked nor explicitly evaluated during the merger process. No sustained collusion was identified during and after these mergers in the Chinese aviation market (Zhang and Round, 2009; Zhang et al., 2014).

3. Research design

The government-guided mergers of Chinese airlines between 2002 and 2004 provide a rare quasi-natural experiment to bypass the endogeneity issue in merger evaluation. We take this opportunity to identify the effects of mergers on airline productivity and costs using the DID approach as our identification strategy.

The first step in implementing the DID identification is to construct a control group of airlines that share similar characteristics to the three Chinese airlines—China Eastern, China Southern, and Air China—operating in both domestic and international markets. The ideal control group should contain similar Chinese airlines that were not affected by the mergers. However, as the mergers grouped all of the largest airlines into the big three, those unaffected were small regional airlines. We therefore use major airlines in Asia, Europe, and North America to construct the control group, which is appropriate for the DID identification for the following reasons. First, the airlines included in our analysis are homogenous in the sense that they are all so-called "full service airlines" that adopt the same business model and similar operational strategies (in terms of aviation networks, pricing strategy/revenue management, fleet composition, airport choice and operation, alliance/code-share practices, frequent flier programs, ticket distribution, etc.). Second, the airlines in our sample are of comparable sizes, and are all leading carriers in their respective home markets (in terms of size and network). They all have growing international services to other major aviation markets, and are members of major global airline alliances. Finally, one major objective of the government-guided mergers in China was to create firms that could compete with major foreign airlines. The Chinese regulators

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[7] These mergers were first ratified by the State Council in the "Civil Aviation System Reform Programme" on Mar 3, 2002 (Zhang and Round, 2008), and the Civil Aviation Administration of China subsequently announced the creation of the "Big Three" airline groups on Oct 11, 2002 (Shaw et al., 2009).

and airlines have used the airlines included in our control group as benchmarks. We conduct also two sensitivity analyses on the validity of the control airlines. Only Asian airlines and only North American airlines are included into the control group in the analyses. Changing the control airlines has little impact on our baseline results. The airlines included in our analysis are reported in Table 1, with summary statistics in 2001, 2005 and 2010 provided in Table 2.

The next step in implementing the DID identification is to compile data from both treated and control airlines in both pre-merger and post-merger periods. The annual reports of the airlines are main data source. We use the calendar year in our analysis, although a few carriers have different financial years. Most airlines in our sample have subsidiary airlines, which are included in our analysis if the corresponding revenues and costs are included in the sample airlines' annual reports. Because the mergers of Chinese airlines were completed in 2004, we use 3 years before 2004 as the pre-merger period and 7 years after 2004 (including 2004) as the post-merger period. For better estimation and identification it would be good to have more data in the pre-merger period. However, many data items for Chinese airlines are not available before 2001. Related details are summarized in Table 1.

We cross-checked the annual reports using additional data sources.[8] These references include the International Civil Aviation Organization databases, the financial and operational data reported by the Bureau of Transportation Statistics in the United States, and the Statistical Data on Civil Aviation in China issued by the Civil Aviation Administration of China. We obtained aircraft leasing prices from Avmark, a company that specializes in aircraft leasing and financing data analysis. A brief description of the data items is provided below and further details can be found in Wang et al. (2014).

- ***Output 1***. Total passenger services: scheduled and non-scheduled operations measured in Revenue-Passenger-Kilometers (RPK), converted to Revenue-Ton-Kilometers (RTK).
- ***Output 2***. Total freight services: scheduled and non-scheduled operations measured in RTK.
- ***Output 3***. Incidental services: a catch-all item for all output not included in passenger and freight services, such as catering, ground handling, aircraft maintenance for other airlines, consulting, and hotel business.
- ***Input 1***. Labor: yearly number of full-time employees.
- ***Input 2***. Fuel: gallons of jet fuel consumed.
- ***Input 3***. Flight equipment: number of aircraft by type. Using leasing prices as weights, different types of aircraft are aggregated into a fleet quantity index using the translog multilateral index procedure proposed by Caves et al. (1982) and Oum et al. (2005) for the TFP calculation.

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[8] The complete dataset was reviewed by researchers at the Academy of Civil Aviation Science and Technology in Beijing, which publishes the official statistics for the aviation operations of Chinese airlines.

Table 1
List of airlines included.

Airline group	Fiscal year	Airlines included in annual reports
China Eastern	Jan 1 to Dec 31	China Eastern Airlines China Northwest Airlines (since Jan 1, 2005) China Yunnan Airlines (since Jan 1, 2005) Shanghai Airlines (since Jan 1, 2010)
China Southern	Jan 1 to Dec 31	China Southern Airlines China Northern Airlines (since Jan 1, 2005) China Xinjiang Airlines (since Jan 1, 2005)
Air China	Jan 1 to Dec 31	Air China Airlines China Southwest Airlines (since Jan 1 2001) CNAC (since Jan 1 2001) Shenzhen Airlines (since Apr 20, 2010)
Thai Airways	Oct 1 to Sep 30	Thai Airways
Singapore Airlines	Apr 1 to Mar 30	SIA SIA Cargo SilkAir
Cathay Pacific	Jan 1 to Dec 31	Cathay Pacific Airways (including cargo operation) Air Hong Kong Dragon Air (since Oct 1, 2006)
AMR	Jan 1 to Dec 31	American Airlines AMR Eagle: American Eagle, Executive airlines
Delta	Jan 1 to Dec 31	Delta Airlines Comair ASA (not included since Sept 2005) Northwest (since Oct 30, 2008)
United	Jan 1 to Dec 31	United Airlines United Express (since Jan 1, 2010) Continental airlines (since Oct 1, 2010)
Continental (2001–2009)	Jan 1 to Dec 31	Continental airlines Expressjet
Air Canada	Jan 1 to Dec 31	Air Canada Jazz Air, ZIP, Air Canada Tango Canadian Air
Lufthansa	Jan 1 to Dec 31	Lufthansa Airlines Lufthansa's regional carriers SWISS (since Mar 2005) Austrian airlines (since Sep 2009) British Midland airlines (since Nov 2009)
Air France (2002–2004)	Apr 1 to Mar 31	Air France Brit Air, Cityjet, Regional
KLM (2001–2004)	Apr 1 to Mar 31	KLM Cityhopper, Cityhopper UK
Air France- KLM (2005–2010)	Apr 1 to Mar 31	Air France group KLM group

Table 2
Descriptive statistics of the sample airlines.

(a) Year 2001

Airlines	Revenue (1000 USD)	Fuel cost (1000 USD)	RPK (1000 RPK)	No. of employee	Passenger revenue (%)	Cargo revenue (%)	Incidental revenue (%)	Load factor (%)	No. of aircraft
Asia Pacific									
China Eastern	1468,250	315,714	15,815,556	13,500	78.9	17.2	3.90	61.6	70
China Southern	2039,328	428,758	24,839,900	16,368	89.2	8.3	2.48	62.5	111
Air China	2746,915	578,318	28,505,556	25,576	79.4	14.5	6.11	61.9	114
Thai Airways	2907,201	507,832	45,811,111	25,963	78.4	16.4	5.23	74.7	81
Singapore airlines	5482,434	999,541	78,732,994	28,336	70.0	21.5	8.5	76.8	93
Cathay Pacific	3902,677	681,263	47,366,667	16,101	67.6	27.4	5.0	71.3	78
North America									
American Airlines	18,963,000	2888,000	222,323,721	104,898	90.5	3.5	6.0	77.9	1157
Delta	13,879,000	1817,000	181,886,271	76,273	93.4	3.6	2.9	68.8	814
United	16,138,000	2476,000	208,562,042	84,000	85.4	4.4	10.2	70.8	543
Continental	8969,000	1229,000	115,386,388	42,900	94.3	2.6	3.1	71.8	522
Air Canada	6205,606	1028,564	78,200,000	37,476	84.5	6.0	9.5	72.0	400
Europe									
Lufthansa	14,934,989	1450,546	101,171,111	87,975	59.1	14.3	26.6	71.5	345
KLM	4489,445	928,851	67,077,778	33,763	72.1	15.9	12.0	79.8	386

(b) Year 2005

Airlines	Revenue (1000 USD)	Fuel cost (1000 USD)	RPK (1000 RPK)	No. of employee	Passenger revenue (%)	Cargo revenue (%)	Incidental revenue (%)	Load factor (%)	No. of aircraft
Asia Pacific									
China Eastern	3431,829	1084,761	36,380,580	29,301	76.0	18.1	5.9	69.39	180
China Southern	4673,117	1455,765	61,923,000	34,417	89.6	8.1	2.3	70.10	261
Air China	4672,869	1437,231	52,404,800	30,592	82.5	9.7	7.8	74.20	174
Thai Airways	4039,973	1146,210	49,931,000	25,876	79.5	15.7	4.8	71.50	87
Singapore airlines	7217,567	1617,943	77,593,700	28,323	66.5	23.8	9.6	74.10	114
Cathay Pacific	5716,998	2004,286	65,110,000	17,541	68.1	28.9	3.0	78.70	102
North America									
American Airlines	20,712,000	5615,000	237,088,558	88,400	90.6	3.8	5.6	78.02	1001
Delta	16,480,000	4466,000	193,047,250	55,700	88.5	3.2	8.3	76.50	649
United	14,950,000	4032,000	183,902,958	57,000	86.4	4.9	8.7	81.40	460
Continental	11,208,000	2443,000	129,067,779	39,530	91.3	3.7	5.0	78.90	622
Air Canada	7805,154	1813,060	75,256,144	27,425	86.7	6.6	6.7	79.50	312
Europe									
Lufthansa	22,465,552	3310,451	108,184,500	90,811	62.6	14.3	23.0	75.00	432
Air France-KLM	24,209,073	3383,823	168,998,000	102,077	79.0	13.2	7.8	78.70	568

(c) Year 2010

Airlines	Revenue (1000 USD)	Fuel cost (1000 USD)	RPK (1000 RPK)	No. of employee	Passenger revenue (%)	Cargo revenue (%)	Incidental revenue (%)	Load factor (%)	No. of aircraft
Asia Pacific									
China Eastern	10,901,141	3191,249	92,116,778	57,096	79.9	11.4	8.7	80.0	355
China Southern	11,298,665	3469,877	110,084,000	65,085	89.8	7.1	3.1	79.2	406
Air China	12,183,790	3559,102	105,039,000	52,108	82.6	12.2	5.2	80.1	347
Thai Airways	5699,374	1783,735	56,688,889	25,884	80.2	15.6	4.2	73.6	90
Singapore airlines	9319,562	3076,255	93,598,592	33,222	62.1	18.1	19.8	78.4	136
Cathay Pacific	11,201,853	3639,515	102,200,000	23,631	68.2	29.8	2.0	83.4	167
North America									
American Airlines	22,170,000	6400,000	240,146,312	78,250	86.1	3.0	10.9	81.2	914
Delta	31,755,000	7594,000	345,417,079	79,684	85.8	2.7	11.5	83.0	815
United-Continental	23,229,000	6687,000	251,874,853	56,000	87.4	3.6	9.0	83.1	753
Air Canada	10,470,190	2574,350	92,760,800	23,838	87.4	4.3	8.3	81.7	328
Europe									
Lufthansa	36,188,572	6831,381	206,022,222	117,066	70.2	11.3	18.5	79.3	710
Air France-KLM	27,804,965	6257,905	224,950,000	104,772	77.5	11.6	10.9	80.7	625

Source: Company's annual reports.

Note: The data for Air France in year 2001 is unavailable. United and Continental merged in year 2010 and the data is combined.

- ***Input 4***: Ground property and equipment (GPE): the capital stock of GPE is reported in airlines' financial reports. A GPE price index is obtained using the method proposed by Christensen and Jorgenson (1969).
- ***Input 5***. Material inputs: this is a catch-all item for all other inputs and costs.

As the GPE cost is much smaller than the fleet equipment cost, the GPE and fleet equipment costs are categorized together as a single capital input in the TFP calculation. Both the quantities and the corresponding revenues/costs are compiled for the inputs and outputs listed above; for example, the volumes and costs of jet fuel are compiled. The only exception is flight equipment, for which market leasing prices are used.

4. Empirical approach

We use the following regression equation to implement the DID estimation:

$$y_{it} = \alpha \times Merger_{it} + \mathbf{X}_{it}\mathbf{B} + \mathbf{Z}_i\gamma + \varphi \times Trend + \theta_i \times Trend + c_i + \varepsilon_{it} \qquad (1)$$

where y_{it} is the efficiency outcome of airline i in year t; $Merger_{it}$ is a dummy variable that takes the value of one if i represents one of the three Chinese Airlines and t is after the merger event; $\mathbf{X}_{it}$ is a vector of the time-varying explanatory variables that affect the efficiency outcome of interest; $\mathbf{Z}_i$ is a vector of the time-invariant explanatory variables, such as country dummies; $\varphi \times Trend$ captures technology changes in the airline industry that are common to all airlines; $\theta_i \times Trend$, with θ_i as a random value, allows each airline to have its own time path of efficiency change; finally, the random individual effects (c_i) capture the time-invariant unobserved individual heterogeneity in efficiency. Our research question focuses on the estimate of α.

A simple OLS regression of Eq. (1) leads to inconsistent estimates because the regressors are expected to be correlated with both random individual trends and time-invariant random individual effects. Let Δ denote the first-order difference operator, and we have

$$\Delta y_{it} = \alpha \times \Delta Merger_{it} + \Delta\mathbf{X}_{it}\mathbf{B} + \varphi + \theta_i + \Delta\varepsilon_{it} \qquad (2)$$

The remaining individual effects in Eq. (2) can be further removed by demeaning

$$\Delta y_{it} - \Delta\bar{y}_{i\cdot} = \alpha\left(\Delta Merger_{it} - \Delta\overline{Merger}_{i\cdot}\right) + \left(\Delta\mathbf{X}_{it} - \Delta\bar{\mathbf{X}}_{i\cdot}\right)\mathbf{B} + \left(\Delta\varepsilon_{it} - \Delta\bar{\varepsilon}_{i\cdot}\right) \qquad (3)$$

where $\Delta\bar{y}_{i\cdot} = \frac{1}{R-1}\sum_{t=1}^{R-1}\Delta y_{it}$ and R denotes the number of years in the panel data; $\Delta\bar{\mathbf{X}}_{i\cdot}$, $\Delta\overline{Merger}_{i\cdot}$, and $\Delta\bar{\varepsilon}_{i\cdot}$ are defined in the same way. Eq. (3) is free of individual time trends and individual effects, so the remaining parameters can be consistently estimated by OLS regression given that the merger of Chinese airlines was imposed by the government. In our empirical analysis, we use the estimate of α from Eq. (3) to infer the effect of merger on airline efficiency.

A merger could affect not only the level of efficiency, but also the change in the efficiency level. To account for this possibility, we also estimate a variation of model 1 as

$$
\begin{aligned}
y_{it} &= \alpha \times Merger_{it} + \delta \times Merger_{it} \times Trend \\
&\quad + \mathbf{X}_{it}\mathbf{B} + \mathbf{Z}_i\gamma + \varphi \times Trend + \theta_i \times Trend + c_i + \varepsilon_{it}
\end{aligned} \tag{4}
$$

Let $MT_{it} = Merger_{it} \times Trend$; differencing and demeaning of this equation leads to the following estimable regression equation:

$$
\begin{aligned}
\Delta y_{it} - \Delta \bar{y}_{i\cdot} &= \alpha\big(\Delta Merger_{it} - \Delta\overline{Merger}_{i\cdot}\big) + \delta\big(\Delta MT_{it} - \overline{\Delta MT}_{i\cdot}\big) \\
&\quad + \big(\Delta \mathbf{X}_{it} - \Delta \bar{\mathbf{X}}_{i\cdot}\big)\mathbf{B} + (\Delta\varepsilon_{it} - \Delta\bar{\varepsilon}_{i\cdot})
\end{aligned} \tag{5}
$$

The OLS estimates from Eq. (5) give us consistent estimates on the effects of merger on both the efficiency level and the change in the efficiency level.

We use both a nonparametric approach, in which Eq. (1) is the log-linear TFP regression and the dependent variable is computed natural log of TFP of the airlines, and a parametric approach, in which Eq. (1) is specified as a translog total cost function of the airlines. We compare the results from these two approaches and draw robust findings from the comparison.

In the nonparametric analysis, the TFP computation method is identical to that of Wang et al. (2014), which follows the approach adopted by Windle and Dresner (1992), Oum and Yu (1995), and Oum et al. (2005). The output and input variables described above are aggregated into a multilateral output and a multilateral input index, respectively, following the translog multilateral index procedure

$$
Q_i = \prod_k \left(\frac{Q_{ki}}{\tilde{Q}_k}\right)^{\frac{(R_{ki}+\bar{R}_k)}{2}}, \quad Q_j = \prod_k \left(\frac{Q_{kj}}{\tilde{Q}_k}\right)^{\frac{(R_{kj}+\bar{R}_k)}{2}} \tag{6.1}
$$

$$
S_i = \prod_p \left(\frac{S_{pi}}{\tilde{S}_p}\right)^{\frac{(W_{pi}+\bar{W}_p)}{2}}, \quad S_j = \prod_p \left(\frac{S_{pj}}{\tilde{S}_p}\right)^{\frac{(W_{pj}+\bar{W}_p)}{2}} \tag{6.2}
$$

where i and j denote different airlines and time periods, respectively, and

Q_{ki} is the output k for observation i;
R_{ki} is the revenue share of output k for observation i;
$\bar{R}_k$ is the arithmetic mean of the revenue shares of output k over all observations;
$\tilde{Q}_k$ is the geometric mean of output k over all observations;
S_{pi} is the input p for observation *i;*
W_{pi} is the input cost shares of input p for observation i; and
$\tilde{S}_p$ is the geometric mean of input p over all observations.

TFP is defined as the ratio of the output index to the input index, or $TFP_i/TFP_j = \frac{T_i}{T_j}/\frac{S_i}{S_j}$.

In the parametric approach, we estimate the total costs of airline i in year t as $C_{it} \equiv f(\mathbf{Q}_{it}, \mathbf{W}_{it})$, which is the function of a vector of output quantities ($\mathbf{Q}_{it}$) and a vector of input prices ($\mathbf{W}_{it}$). The log of the total cost function is approximated using the translog functional form, such that we have an empirical cost equation as in Eq. (1), in which y_{it} is the log of the total costs of airline i in year t, and $\mathbf{X}_{it}$ is the vector including the log of output and input prices and their interactions. Other control variables in Eq. (1) capture the heterogeneity across airlines and across time in the airlines' total costs. The coefficient of the merger dummy, α, measures the effect of the merger on the airlines' total costs; a negative α indicates that the merger reduced the total costs of the Chinese airlines by improving their productivity.

Because the cost shares of inputs contain information on the cost parameters, the precision of the cost parameter estimates can be improved by incorporating input share equations in the estimation. By Shephard's lemma, the share of input g in the total cost is $s_{it}^{g} = \frac{\partial \ln C_{it}(\mathbf{Q}_{it}, \mathbf{W}_{it})}{\partial \ln w_{it}^{g}}$, where w_{it}^{g} is the price of input g for airline i in year t. Applying Shephard's lemma to Eq. (1), we have the following input share equations:

$$s_{it}^{g} = \mathbf{X}_{it}^{g}\mathbf{B}^{g} + \lambda_{i}^{g} + \nu_{it}^{g}, g = 1, 2, 3, 4 \tag{7}$$

where $\mathbf{X}_{it}^{g}$ is a subset of $\mathbf{X}_{it}$ and $\mathbf{B}^{g}$ is a subset of $\mathbf{B}$, and λ_{i}^{g} is the individual effects accounting for the panel nature of the data. We specify the individual effects as random to be consistent with the cost equation. To avoid the singularity problem, three of the four input share equations can be jointly estimated along with Eq. (1) as a system of equations. The estimation results are invariant to the choice of share equation. As such, our empirical model to identify the causal effects of mergers on airline costs comprises four equations—the translog total cost in Eq. (1) and the three input share equations denoted by Eq. (7). The four equations contain common cost parameters.

Following the same strategy of differencing and demeaning in estimating the TFP equation, we obtain an estimable cost equation that is free of individual effects and individual time trends, as in Eq. (3). The random individual effects in the input share equations can be removed by demeaning as follows:

$$s_{it}^{g} - \bar{s}_{i\cdot}^{g} = \left(\mathbf{X}_{it}^{g} - \bar{\mathbf{X}}_{i\cdot}^{g}\right)\mathbf{B}^{g} + (\nu_{it}^{g} - \bar{\nu}_{i\cdot}^{g}) \tag{8}$$

The cost equation in (3) and the three input share equations in (8) constitute a system of equations that should be jointly estimated to account for the common parameters in the equations. We estimate the system of equations using a GMM approach, in which the moment functions are the orthogonal conditions between the regressors and error terms in Eqs. (3) and (8), and the weighting matrix accounts for both within-equation and cross-equation correlations between error terms from the same airlines. We specify that the correlations among the errors have a general or unstructured pattern. As such, the identification of the cost system is robust in the sense that it does not rely on a distribution assumption for the error terms and it does not impose restrictions on

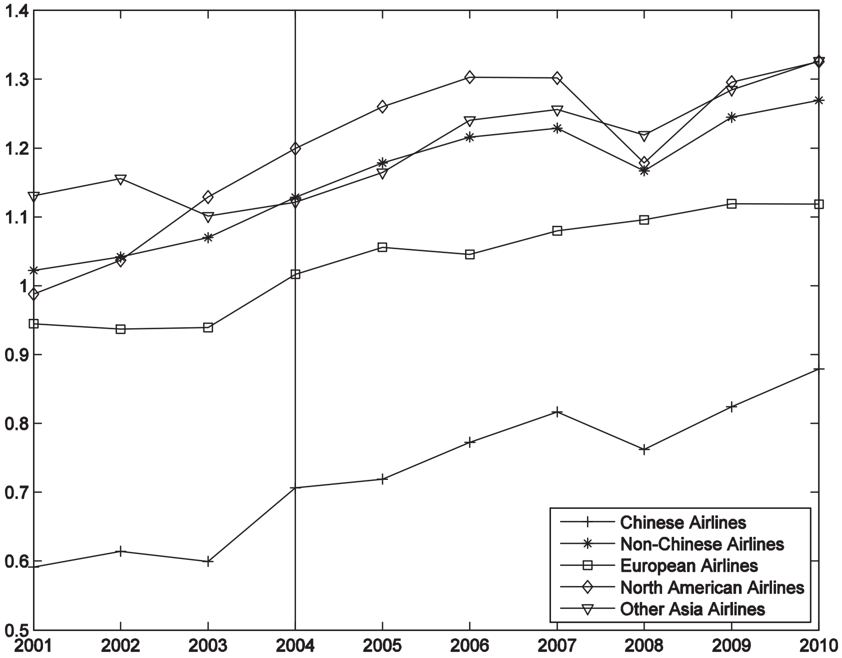

Fig. 1. Change in TFP over time. Note: The vertical line indicates the year when the forced merger of Chinese Airlines occurred. The merger occurred in Nov 2003, so the annual report of 2004 was the first annual report after the merger.

the variance–covariance matrix of error terms as in the seemingly unrelated regression specification.

5. Results

Before presenting the findings from the formal DID analyses, we first present the average TFP values for both the Chinese airlines and the control airlines from 2001 to 2010 in Fig. 1. The government-guided mergers among Chinese airlines were first announced in 2002 and the actual integrations were completed in 2004. Fig. 1 indicates that there was a clear upward trend in the average TFP value of Chinese airlines after 2003.

Although the increased TFP of Chinese airlines is evidence of the positive effect of the mergers on the productivity of the airlines, it may be due to the time trend of technology changes in the industry. In the DID estimation, this time trend is removed by using the productivity change in the control group. The identification assumption of the DID approach is that the productivity changes in treated and control airlines would follow the same time trend if there were no mergers. One simple check for the validity of the identification assumption is to compare the TFP change of the control airlines with that of the treated airlines in the pre-merger period. Fig. 1 plots the TFP change of the airlines included in the control group. If we partition the control group into North

Table 3
Difference-in-differences regression results on the effect of merger on airline TFP (dependent variable: log TFP).

	(1) Full sample	(2) Full sample with time trend	(3) Drop observations after 2007	(4) Excluding non-Asian airlines from the control group	(5) Keeping only North-American airlines in the control group
Merger dummy	0.1346	0.1573	0.1324	0.1573	0.1219
	(0.0297)	(0.0291)	(0.0338)	(0.0311)	(0.0306)
Merger dummy × Time trend		0.0302			
		(0.0110)			
Number of observations	125	125	83	54	72

Note: Numbers in parentheses are standard errors clustered at the airline level.

American, European and Asian airlines, we can see that the TFP of the three Chinese airlines and that of the Asian airlines included in the control group follow very similar dynamics in the pre-merger period. We use the complete control group in the baseline DID estimation, and then use only Asian airlines in the control group to implement the DID estimation in the robustness checks.

Table 3 presents the DID estimates of the effect of merger on TFP, based on Eqs. (3) and (5). Log TFP is the dependent variable and the control variables include time trends and time-invariant variables such as country and airline dummies, which are removed by differencing and demeaning. The post-merger period for the Chinese airlines in the baseline regressions reported in Table 3 is 2004–2010. Models 1 and 2 present the estimates for the full sample and the results indicate that the mergers significantly increased both the level of TFP and the growth rate of TFP of Chinese airlines. Because airlines from different countries may have been affected differently by the financial crisis in 2008, we drop all observations after 2007 in model 3. We exclude non-Asian airlines from the control group in model 4. Model 5 uses the US and Canadian carriers exclusively as the control group—like Chinese airlines, these North American carriers rely much more on domestic services than international services. The positive effect of merger on the TFP of Chinese airlines is robust with respect to variations in the estimation sample.

The complete effect of a merger on airline efficiency may not be realized until several years after the merger. By specifying the post-merger period as the years immediately following the consolidations, the baseline regressions in Table 3 may capture transitional effects of the mergers. In an additional set of robustness checks, we change the definition of the post-merger period and drop the observations in the transition period. The results of these robustness checks are presented in Table 4. We find a larger effect of merger on airlines' TFP if we define the post-merger period as between 2 and 5 years after the merger.

In sum, from the TFP regressions we find a significantly positive effect of merger on the TFP of Chinese airlines. The results reported in Tables 3 and 4 show that the mergers in 2003 increased the TFP of Chinese airlines in subsequent years by 13–29%.

Table 4
Robustness of difference-in-differences TFP regression results to different post-merger periods.

	(1) Post-merger period: 2005–2010; observations in 2004 dropped	(2) Post-merger period: 2006–2010; observations in 2004–2005 dropped	(3) Post-merger period: 2009–2010; observations in 2004–2008 dropped	(4) Post-merger period: 2009–2010; observations in 2004–2008 dropped; non-Asian airlines excluded from control group
Merger dummy	0.1476	0.2246	0.2894	0.2893
	(0.0313)	(0.0425)	(0.0262)	(0.0280)
Number of observations	111	97	55	24

Note: Numbers in parentheses are standard errors clustered at the airline level.

Tables 5–7 report the findings from the parametric approach; that is, the estimates from the translog cost regression. In the baseline specification, the translog cost equation is specified as in Eq. (1) and we estimate it along with three input share equations jointly. The results from the baseline specification are presented in Table 5. All of the cost parameter estimates have the expected signs. The airlines' total costs are most sensitive to the change in passenger services among the three outputs and to the changes in fuel and material prices among the four inputs. We conduct a hypothesis test based on the baseline estimates and cannot reject the null hypothesis that the airlines' production technology exhibits a constant returns to scale.

The estimated coefficient of the merger dummy in the cost equation is the DID estimate of the effect of merger on airlines' total costs. The baseline estimate indicates that the merger caused the total costs of the affected airlines to decrease by about 9%. We conduct the same robustness checks as in the non-parametric TFP regressions for the baseline findings and the results are presented in Tables 6 and 7. All of the robustness checks indicate cost reductions following the airline mergers and the effect of merger on airline costs is significant in most of the robustness checks. The effect of merger on airline costs is especially large and significant if we drop observations from 2004 to 2008 and define the post-merger period as 2009–2010. This evidence suggests that the effect of a merger on the airlines' costs emerges several years later because the affected airlines need time to optimize their operations after the merger.

The Chinese aviation industry has been progressively deregulated and liberalized in the past three decades (Zhang and Round, 2008; Adler et al., 2014; Wang et al., 2016). By 2004, the ownership and management of airports, other than those in Tibet and Beijing, were transferred from central to local governments. Wang et al. (2016) provided a nice overview of the regulatory and competitive changes of the Chinese market. Their competition analysis also suggested that although market concentration increased immediately following the mergers, airline competition increased from 2004 to 2012. It is possible that these changes had contributed to the efficiency improvements identified in our analysis. Because substantial change in market structure occurred in 2002–2004 (because of merger) and in 2005–2007, we estimated our model by dropping the data of 2003. We

Table 5
Baseline difference-in-differences estimates of the effect of merger on airline total cost.[a]

Variables	Estimates (standard errors)[b]
Log of passenger services	0.8719 (0.1013)
Log of freight services	0.0093 (0.0782)
Log of incidental services	0.0182 (0.0537)
Log of capital price	0.1593 (0.0476)
Log of labor price	0.1441 (0.0662)
Log of fuel price	0.3287 (0.0361)
Log of passenger services × log of passenger services	0.0167 (0.1614)
Log of passenger services × log of freight services	0.3098 (0.1340)
Log of passenger services × log of incidental services	−0.0630 (0.0663)
Log of freight services × log of freight services	−0.0128 (0.0709)
Log of freight services × log of incidental services	−0.2202 (0.1013)
Log of incidental services × log of incidental services	0.1659 (0.1050)
Log of capital price × log of capital price	0.0761 (0.0106)
Log of capital price × log of labor price	0.0109 (0.0178)
Log of capital price × log of fuel price	−0.0464 (0.0082)
Log of labor price × log of labor price	0.1249 (0.0349)
Log of labor price × log of fuel price	−0.0872 (0.0105)
Log of fuel price × log of fuel price	0.1935 (0.0150)
Log of passenger services × log of capital price	0.0608 (0.0239)
Log of passenger services × log of labor price	−0.0015 (0.0314)
Log of passenger services × log of fuel price	0.0223 (0.0285)
Log of freight services × log of capital price	−0.0492 (0.0290)
Log of freight services × log of labor price	0.0359 (0.0287)
Log of freight services × log of fuel price	0.0239 (0.0295)
Log of incidental services × log of capital price	−0.0110 (0.0081)
Log of incidental services × log of labor price	−0.0208 (0.0185)
Log of incidental services × log of fuel price	−0.0280 (0.0142)
Merge dummy	−0.0920 (0.0483)
R^2	0.88
Number of airlines	14
Number of equations	4
Number of observations	500

[a] Output and input prices are normalized to their sample means before taking the log.
[b] Standard errors clustered at the airline level.

also tested the cases in which observations after 2005 were further dropped, thus that the post-merger period included only 2004 and 2005. If the change in market structure has a dominant effect on airline efficiency change, estimations results from these alternative specifications are expected to change substantially. However, these alternative specifications for both the TFP and cost function analysis all led to statistically significant and consistent results, which suggest that the findings of our analysis are robust.

Table 6
Robustness checks on the effect of merger on airline total cost.

	(1) Baseline results	(2) With time trend	(3) Observations after 2007 dropped	(4) Non-Asian Airlines excluded from control group	(5) Keeping only North-American airlines in the control group
Merger dummy	−0.0920	−0.1404	−0.0086	−0.0424	−0.1222
	(0.0483)	(0.0488)	(0.0594)	(0.0757)	(0.0461)
Merge dummy × Time trend		−0.0693			
		(0.0214)			
Number of observations	500	500	332	216	288

Note: Numbers in parentheses are standard errors clustered at the airline level.

Table 7
Robustness of cost results to different post-merger periods.

	(1) Post-merger period: 2005–2010; observations in 2004 dropped	(2) Post-merger period: 2006–2010; observations in 2004–2005 dropped	(3) Post-merger period: 2009–2010; observations in 2004–2008 dropped	(4) Post-merger period: 2009–2010; observations in 2004–2008 dropped; non-Asian airlines excluded from control group
Merger dummy	−0.0812	−0.1339	−0.1009	−0.1963
	(0.0938)	(0.0984)	(0.0615)	(0.0671)
Number of observations	444	388	220	96

Note: Numbers in parentheses are standard errors clustered at the airline level.

6. Discussion

This study contributes to the literature by evaluating the effects of mergers on airline efficiency using a quasi-natural experiment in China. Similar airlines in terms of business models and operational strategies in other markets are used as the control group in the DID estimation. As major mergers have been carried out in worldwide aviation markets, our findings may serve as a useful reference for airlines and regulators alike.

Nevertheless, our findings on the positive effects of mergers on airline efficiency should be used with caution in designing public policy. Productivity gains and cost reductions from mergers do not necessarily lead to welfare improvement because market concentration in the post-merger period may boost air fares. A complete merger evaluation should be based on a model incorporating the cost-side analysis with the market structure and demand-side analyses (Nevo and Whinston, 2010). The findings from this study are useful for building such a model. For example, in building an airline competition model to simulate the welfare effects of merger, the 10–20% reduction in airline operation costs identified from the reduced-form approach can be incorporated into the airline competition in the post-merger period. In other words, the identified effect of merger on airline efficiency from the quasi-natural experiment can be used as the parameter in structural models to conduct a comprehensive evaluation of airline mergers.

Great efforts were made to include a control group of non-merging Chinese airlines. However, the lack of comprehensive data on these carriers, which were much smaller and not privatized or listed on stock exchanges, meant that this was not possible. Therefore, we cannot totally rule out the possibility that the observed efficiency gains were due to other major changes in market conditions or regulations. Because the major policy changes, including the removal of price and route entry regulations, were carried out prior to the mergers, it is possible but unlikely that these confounding effects are significant. Finally, although productive efficiency was not explicitly evaluated in the merger process nor emphasized in the official government decisions, it was listed as an important consideration in certain reviews and white papers.[9] As cautioned in the introduction session, the mergers of Chinese airlines were not entirely randomly arranged and thus our analysis shall be regarded as based on a quasi-natural experiment. We hope that our study will lead to more novel research on this important issue.

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[9] See for example, discussions at http://www.reformdata.org/special/245/about.html (in Chinese). We are thankful to one anonymous referee for pointing out this issue to us.

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